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6. AUTHOR(S) Jeremy M Wolfe (PI)					
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9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) Dr. Willard Larkin AFOSR 801 North Randolph Street Room 732 Arlington VA 22203-1977				10. SPONSORING / MONITORING AGENCY REPORT NUMBER	
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The Deployment of Visual Attention: Final Report 1999-2002**F49620-01-1-0071****Jeremy Wolfe****Status of Effort: Abstract**

This is the final report summarizing research on the deployment of attention in visual search. In visual search, observers look for targets among distractor items. Models of search had assumed that items were sampled *without replacement*. Items, rejected as distractors, would not be revisited during the search. Research reported here falsifies that hypothesis. Our data are consistent with sampling *with replacement* – no use of information about rejected distractors. The data do not reject models that posit small amounts of memory for rejected distractors (e.g. don't revisit the last N rejected items; $N < 7$). Why is search so apparently random? Observers could have the benefits of memory for rejected distractors if they searched in an orderly manner (e.g. "reading" a display from left to right). Our second line of experiments shows that the temporal costs of such a strategy are too high. Left to its own devices, covert visual search proceeds at about 20-30 items/second. Commanded shifts of attention proceed at only 3-5 shifts/second. For the tasks used here, anarchic covert search will be faster than commanded, orderly search. Our Guided Search model is adapted readily to search with replacement. Nature may have stumbled on a way to perform sophisticated search tasks with simple tools.

Introduction

This report discusses the work accomplished in our laboratory during the period 1999-2002 with the assistance of funding from the Air Force Office of Scientific Research. There were three main areas of proposed research in this grant period and they will comprise the three main divisions of this report. They are: 1) the role of memory for rejected distractors in visual search, 2) comparison of the speed of volitional and reflexive deployments of attention, and 3) modeling of the deployment of visual search. This report will be fairly brief in its descriptions of our findings. The more detailed accounts can be found in our published and submitted papers.

Memory in visual search

In visual search tasks, observers look for a target item among some number of distractor items. This might be accomplished by deploying attention from item to item in sequential manner or by processing all items in parallel, accumulating evidence that specific items were distractors or targets. For many years, standard "serial" and "parallel" models of visual search had assumed that information accumulated steadily during the course of a search. This was particularly explicit in the case of serial, self-terminating models (e.g. Feature Integration theory and the first versions of Guided Search). (Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989). Those models assumed that attention was deployed from item to item, sampling the display *without replacement* until the target was found or until almost all candidate targets were examined and rejected.

In 1998, we upset this particular apple cart with a paper in *Nature* with the provocative title "Visual search has no memory" (Horowitz & Wolfe, 1998). The experiment was conceptually simple. We had observers perform a typically inefficient search for a "T" among "L"s. We compared the standard static case to a dynamic version in which we replotted all items in new locations every 100 msec. Our reasoning was that this would thwart most strategies for accumulating information during a search. Certainly, it would prevent marking or inhibiting rejected distractors in a sequential manner. Under dynamic conditions, search should proceed *with replacement*. The best that an observer could do would be to grab an item or two at random on each frames. If standard search was search without replacement and dynamic search was sampling with replacement, straightforward probability theory says that the slope of the RT x set size functions, the standard measure of search efficiency, should be twice as great in the dynamic case as in the static. This was not the case. In several versions of the experiment, search efficiency was not significantly different in the two cases (though overall RTs were longer). We concluded that the search process in the two conditions were similar. If dynamic search had to be search with replacement, then standard static search might also be search with replacement. Hence, we argued that visual search had no memory.

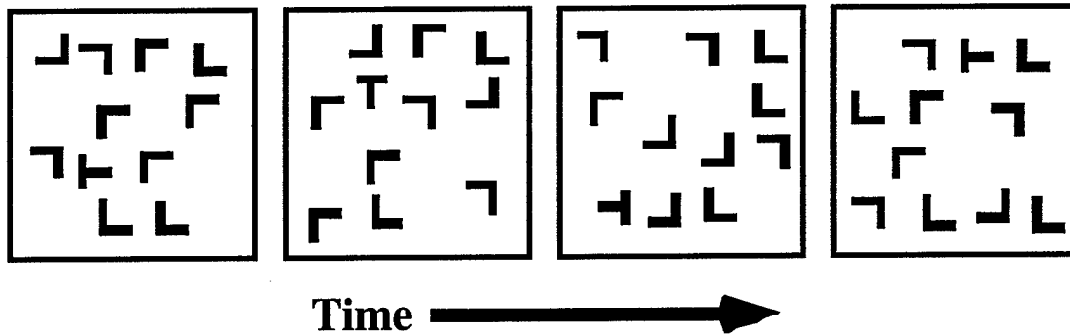


Figure One: In dynamic search, the items are replotted in random locations repeatedly during the course of a search.

This claim provoked a fair amount of controversy. In some cases, this was the result of taking the title of the paper too literally and too sweepingly. For example, we never meant to suggest that observers could not remember when they found a target (Gibson, Li, Skow, Brown, & Cooke, 2000). However, others questioned our actual claim, that visual search was search with replacement (Hollingworth & Henderson, 2002; Kristjansson, 2000; Melcher & Kowler, 2001; Muller & von Muhlenen, 2000; Peterson, Kramer, Wang, Irwin, & McCarley, 2000; Shore & Klein, 2000). Consequently, we have conducted several different series of experiments in order to assess the role of memory in search. To summarize our current thinking, it seems clear that we can reject any model of search that proposes perfect or near perfect sampling without replacement. We cannot reject pure sampling with replacement. However, nor can we reject models with some memory (e.g. models that propose that observers can avoid deploying attention to the last N items visited where N is fairly small number). These partial memory models seem the most promising at the present time (Arani, Karwan, & Drury, 1984).

Dynamic Search Experiments

One problem with a simple dynamic search paradigm is that one would not need to move attention. If items are randomly replotted, one could “sit and wait” for the target to appear. That would produce data that resemble sampling with replacement (von Muhlenen, Muller, & Muller, 2003). We have conducted several versions of the experiment in an effort to thwart ‘sit and wait’ strategies. We have restricted targets to specific radial distances from fixation. The distance changes from trial to trial and the manipulation is not known to the observer. An observer attending at or near fixation (or, indeed, on any single location) would make a disastrous number of errors. Performance was essentially the same as in our other dynamic search tasks. Similarly, we have restricted targets to one quadrant of the field. Von Muhlenen et al (2003) have shown that a sit and wait strategy can mimic our results if it is assumed that observers can “sit” on multiple items. However, at present we believe that the bulk of the data suggest that our basic result is not an artifact of such strategies.

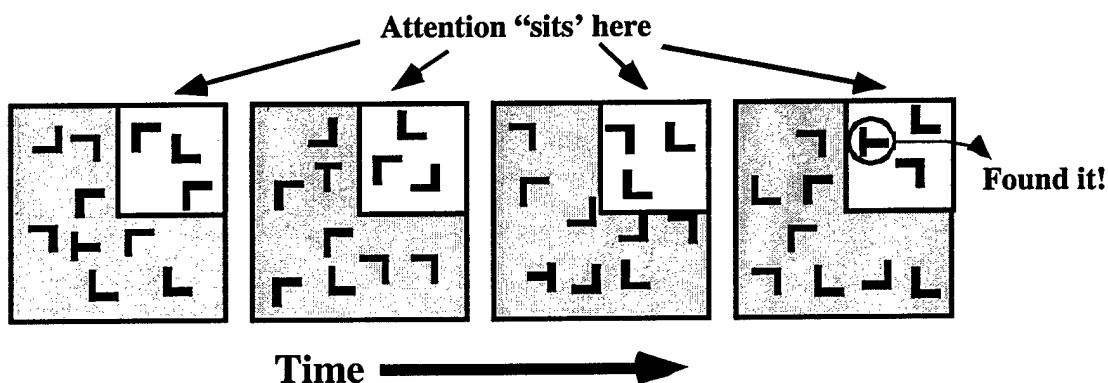


Figure Two: In a ‘sit and wait’ strategy, observers would only monitor a few locations in the display. In this specific instance, that would work.

Arni Kristjansson found different results when he used larger set sizes than those used in our original paper (Kristjansson, 2000). Faced with this issue, we ran a version of the basic experiment with large set sizes. We also slowed the frame rate to 2 Hz in order to decrease the masking effects of rapid change. These slower frame rates cannot be used with small set sizes because search with or without replacement would be finished within a single frame on most trials.

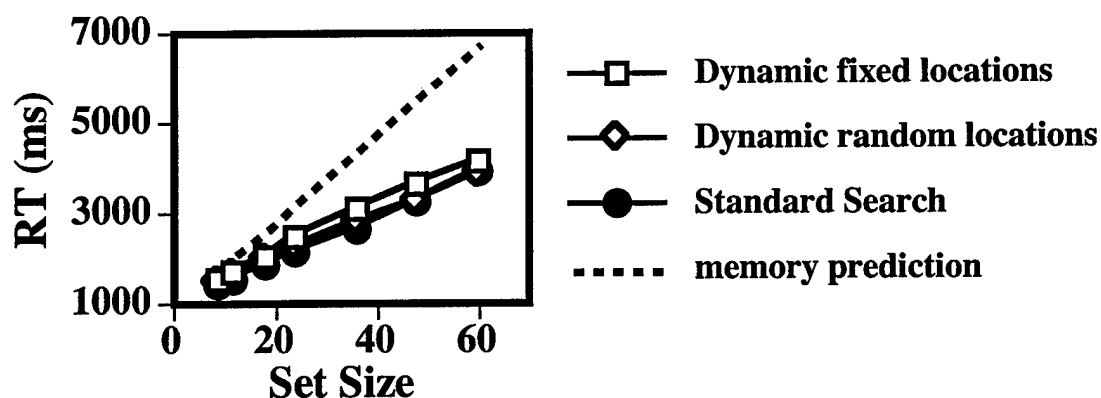


Figure Three: RT x set size functions for standard search for a T among Ls (solid circles) and for two versions of a dynamic search task (open). If standard search is search without replacement, then data from dynamic search (with replacement) should fall on the dashed line, which it does not.

As Figure Three makes clear, there is no significant difference between the Dynamic and Standard conditions of this experiment. The error rates were comparable, as well, in this study. The two dynamic conditions differ in the placement of items. In the “fixed location” condition, the same N locations were used on all frames. In the “random

location" condition, items could be plotted in any screen location on each frame. This did not matter in our study. Kristjansson used a fixed location method and, at a faster frame rate than we used, may have introduced masking effects that slowed his observers in the dynamic condition.

Memory in Search: ART methods

The dynamic search paradigm has the advantage of being immediately comprehensible. If you replot all the items every 100 msec, you cannot keep track of rejected distractors. However, the method has a number of drawbacks. RTs are typically longer in dynamic search. Error rates are higher. These facts complicate the interpretation of the results. In our view, they are directly related to the degrading of the stimulus in the dynamic condition. However, whatever their cause, the problems with the dynamic search paradigm make it important to develop converging evidence from other methods. That has been an important part of the research in the prior grant period.

One set of experiments used what can be called "attentional reaction time (ART)" methods. Our goal was to measure the time at which a target item was found more precisely than can be done with a standard RT technique. The basic method is illustrated in Figure Four

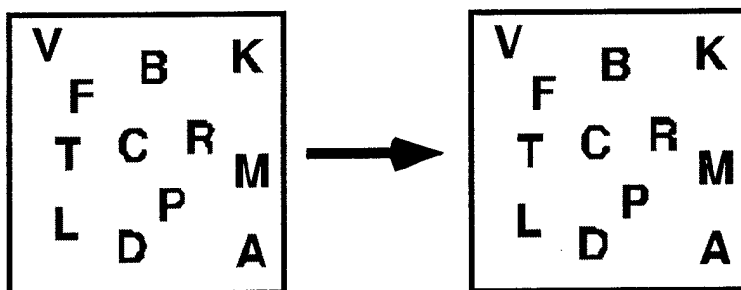


Figure Four: In this version of an ART task, observers could be asked to name the color of a target letter (e.g. F). If the named color was the Frame 1 color, then we know that the target was found before the transition from Frame 1 to Frame 2.

Observers searched for a specific letter (e.g. the “F” in Figure Four). The letter was always present. The observer’s task was to name the color of the letter. At some time during the course of the trial, the color changed (here from purple to blue). Note that the display is otherwise stable. This is not a dynamic search experiment. If the observer reported that the “F” had been purple, then we know that the item was found before the color change. By varying the time of the color change, we estimate the probability of finding a target as a function of time. That estimate can be corrected for guessing by looking at the errors when observers name a color that was neither the Frame 1 nor the Frame 2 color of the target letter.

This method makes qualitatively different predictions for models that propose sampling from the display with and without memory. A cartoon is shown in Figure 5.

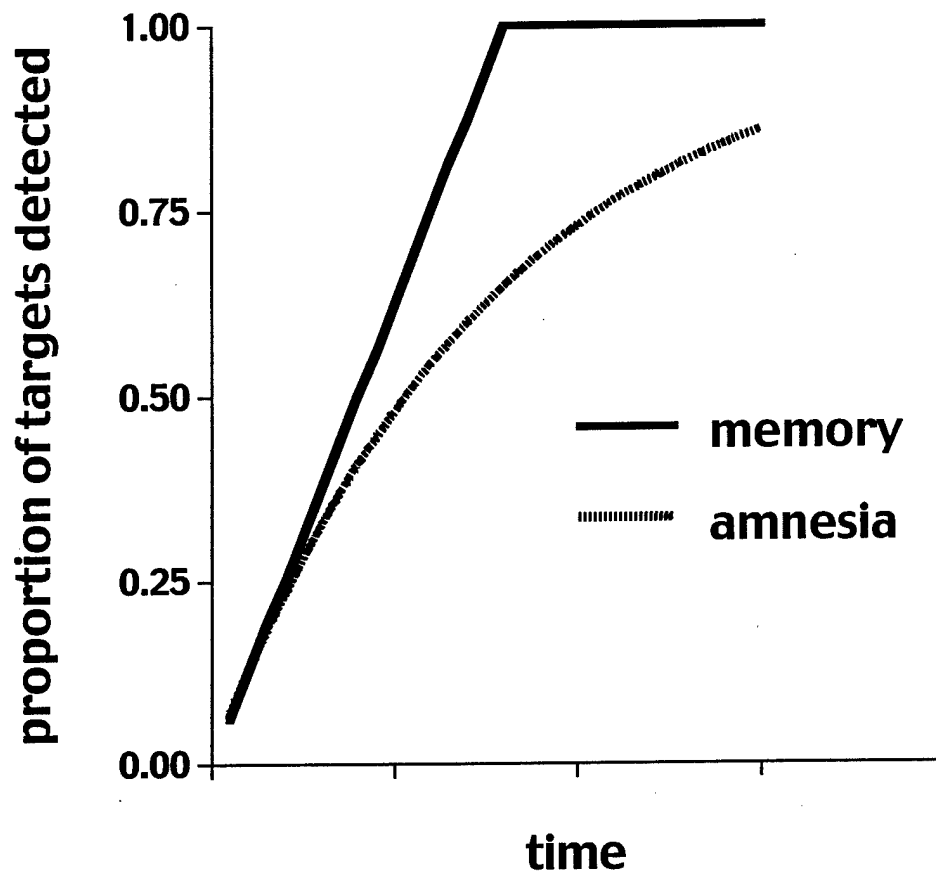


Figure Five: Sampling with replacement (amnesia) predicts an exponential cumulative distribution function (CDF) for the proportion of targets found before a color change. Sampling without replacement predicts a linear CDF.

If observers sample without replacement, then the probability that the target will be found is a linear function of the time. For instance, if there were ten items and one item was processed every 50 msec, then there would be a 10% chance of finding the target in the first 50 msec, 20% in 100 msec and so on. If observers sample with replacement, then the probability of finding the target in any epoch (e.g. 50 msec) is fixed (10% in this

example) and the cumulative probability is an exponential function (0.1^N , where N is the number of epochs).

Some typical data are shown in Figure Six.

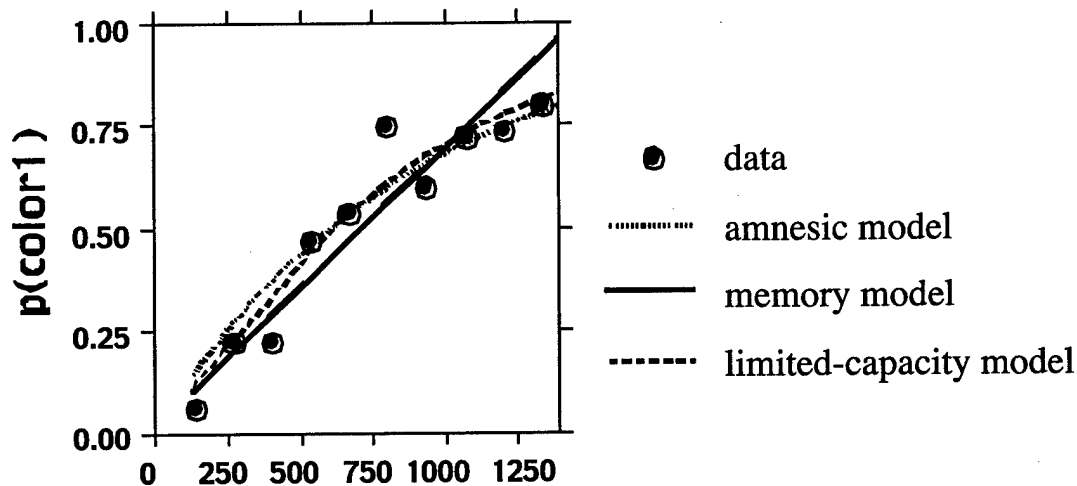


Figure Six: Data from an ART experiment showing probability of correctly naming the initial color of a letter as a function of the time prior to a color change.

It is possible to fit amnesic (with replacement) and memory (without replacement) models to the data. Fits are done by adjusting the rate parameter (how many letters are processed per second). Search with replacement is always a better fit to the data than search without.

That said, it is probably a mistake to see the issue of memory in search as a dichotomous choice between search with and without replacement. There are several families of partial models to be considered. For example, suppose observers can keep track of the last N items and can avoid revisiting them? Alternatively, suppose that observers can keep track

of an average of N items but these are not necessarily the last N items? The results of our experiments rule out models that assume perfect sampling without replacement. However, the results are consistent with a modest memory for rejected distractors. In the ART experiments, N -back models provide good fits to the data for $N < 6$.

Multiple target experiments

In a third line of experiments, we asked observers to count the number of targets in a display. Specifically, on each trial, we asked if there were at least N targets in the display. We varied the actual number of targets in the display. The virtue of this paradigm is that, like the ART paradigm, it produces qualitatively different predictions for search with and without replacement. First, it is important to note that this paradigm is based on the assumption that observers *do* remember targets once they have been found (Gibson et al., 2000). That being the case, consider the situation in an amnesic search, a search with replacement. Each time a target is found there are fewer targets to find. If observers sample at random, then the ratio of targets to distractors gets worse over time. If there were five targets and ten distractors, for example, the observer would have a $5/15=1/3$ rd chance of finding a target at the start of the trial but only a $1/11$ chance by the time four targets had been found. Therefore, RT should be an accelerating function of the number of targets that need to be found.

On the other hand, if observers sample without replacement, then the number of remaining distractors should decline in step with the number of remaining targets. The

theoretical result is a roughly linear increase in RT with number of targets to find. This is shown in Figure 7a.

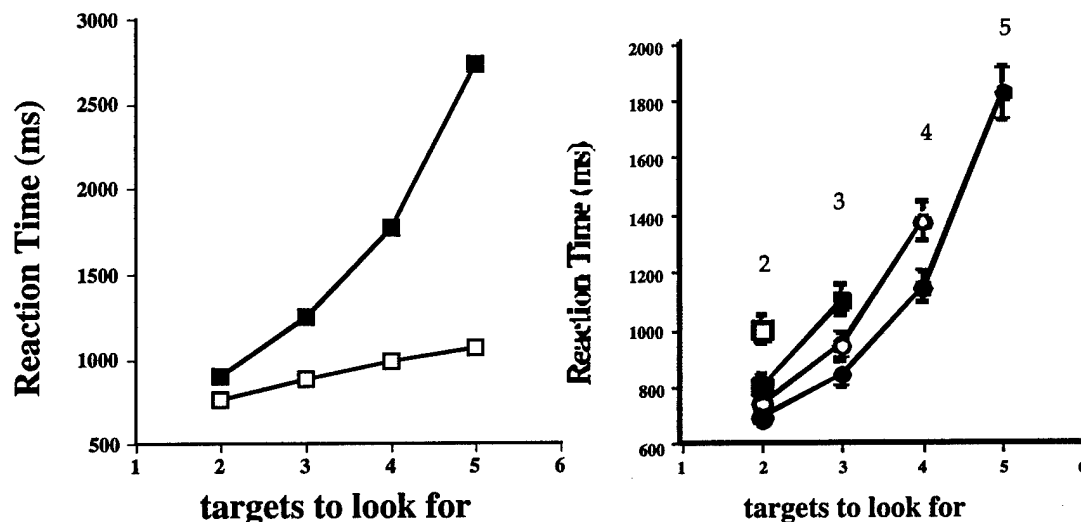


Figure Seven: Hypothetical (left) and actual (right) RTs for an experiment in which observers respond positively if they find N targets. On left, solid symbols are for a model that samples with replacement (amnesia). Open symbols represent sampling without replacement (memory)

Figure 7b shows some of the data. The number above each curve indicates the number of target present in the display. The graphs plot RT as a function of the number of targets that the observer was search for. It is clear that the data in 7b show the accelerating curvature predicted by the amnesic / with replacment model and, indeed, the model fits are stronger for with replacement than for without replacement models. As with our other experiments in this area, the data can be used to reject a model that argues for perfect memory for rejected distractors. The data are consistent with a no memory account. However, the data cannot reject the possibility of some small amount of memory.

This represents the current state of our thinking in this area. We cannot find convincing empirical support for the presence of memory in covert visual search. At the much slower time course of overt deployments of the eyes, there is some evidence for memory from other labs (e.g. Hollingworth & Henderson, 2002; Melcher & Kowler, 2001; Peterson et al., 2000). Because of the range of possible models (Arani et al., 1984) (Horowitz & Wolfe, 2003), it has proven difficult to date to design experiments that can clearly distinguish between no memory for rejected distractors and a little memory. This is an area of ongoing work.

The Costs of Attentional Strategy

Why not make use of memory for rejected distractors in search? A change in one line of code is all that it takes in computer models of search. Given that memory would produce a two-fold improvement in search efficiency, why not use it? A reasonable guess would be that there is some cost to keeping track of where you have been that more than eliminates the benefits of doing so. Direct evidence for the cost of holding distractors in memory is not presently available. However, we have shown a substantial cost for a "short-cut" that would mimic memory. If observers searched a display in an orderly manner (left to right, center to periphery), this would mimic memory. If you are searching for a word on a page by reading from left to right, for instance, you will find the target word, if present, on average after reading half the page. In this case, you only need to remember where you are currently and the rule for getting to the next place.

We asked about the time course of such volitional deployments of attention. In a series of experiments, we forced subjects to move their attention in a specific manner. Figure Eight shows a schematic of such a task.

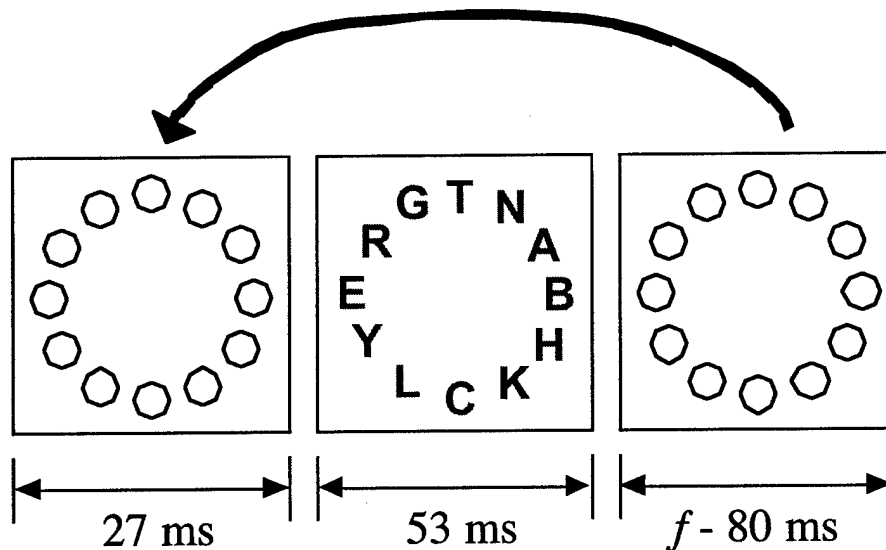


Figure Eight. One cycle of twelve in the commanded search experiment. 27 ms of metacontrast mask is followed by a 53 msec letter display and a post mask

In this task, observers are asked to move their attention around a ring of items at a fixed rate. The task is to report the color of the letter "Y". The items change from frame to frame with the "Y" appearing only on frame N. On frame N, the "Y" appears in position N. The observer starts at position zero. Suppose that the target appears in position 8 at frame 8. After 8 frames, the observer should have deployed attention to position 8 and, thus, be able to perform the task. If the deployments were not keeping pace with the frame rate, the observer would need to guess. We varied the frame rate using a staircase procedure to estimate a 67% threshold duration for this "Commanded" search. The whole display lasted for 12 frames. We compared this to a control condition with targets present

on all 12 frames. This permitted free "anarchic" visual search and allowed us to estimate the speed of deployment when attention was not constrained to move from location to location in a fixed order. The Commanded search threshold averaged 274 msec per deployment. The Anarchic threshold was only 85 msec/item which is very close to the floor value of 80 msec in this particular design.

In order to eliminate the need to switch deployment rate from trial to trial, we repeated the experiment with frame duration fixed a point $2/3^{\text{rd}}$ of the temporal distance between the shorter Anarchic staircase threshold and the longer Commanded condition. Accuracy in the Anarchic condition was near ceiling (97%). Accuracy in the Anarchic condition was much worse (66%).

We have performed several variants and control experiments using this basic paradigm and we find that estimates of the speed of Commanded deployments of attentional are always markedly slower than Anarchic deployments. Details can be found in Wolfe, Alvarez, and Horowitz (2000) and our submitted manuscript on this topic (Horowitz, Wolfe, and Alvarez, submitted).

This method has some of the limitations of the dynamic search tasks. Stimuli are flickering on and off. There are masks. While we have attempted to control for factors other than visual attention deployment speed, the situation is complicated. Accordingly we have tried to gain converging evidence from another method. The alternate method is shown in Figure 9, below.

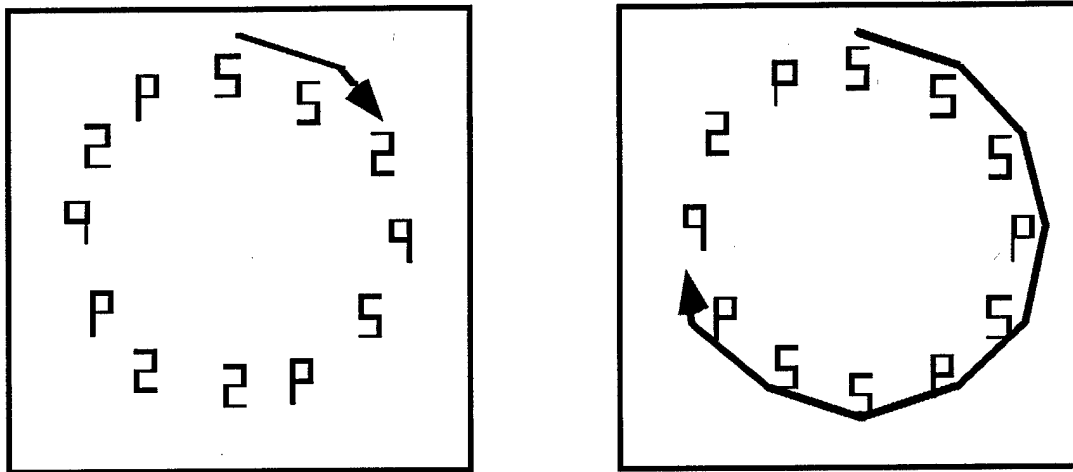


Figure Nine: Observers were instructed to report the identity of the first mirror reversed letter starting at 12 o'clock and moving clockwise. Position around the circle is analogous to set size in this paradigm.

In this task, observers were asked to find the first mirror-reversed letter and to identify it as an S or a P. "First" was defined by asking observers to begin at 12 o'clock at the top of the circle and find the first target as they proceeded clockwise around the circle. Since there can be multiple mirror-reversed items on each trial, this strongly encourages observers to move attention in a fixed path around the circle. Target distance around the circle serves the same role as set size in a standard search task. In Figure 9a, the observer makes 2 deployments before finding the target. In 9b, the observer makes nine deployment. $(RT_9 - RT_2)/7$ gives an estimate of rate of deployment.

In the actual experiment, set sizes of 7, 9, and 11 were used. The rate of deployment is estimated by the slope of the function relating RT to target position around the circle of items. Note that, in this condition, RT should be dependent only on serial position around

the circle, not on set size. A target in position 5 should be found after five deployments regardless of the number of items in the display as a whole.

For comparison, we ran an Anarchic condition with the same set sizes. In this case, there was only one mirror-reversed letter per display and observers were simply told to find it. They were explicitly told that they did not need to search in any specific order. In this condition, RT should not be dependent on position around the circle. However, it should be dependent on set size in the usual manner of visual search experiments.

The data are shown in Figure Ten. Fig. 10a shows the results for the Anarchic condition. Note that the RTs do not depend on target position. However, as would be expected, the RTs for smaller set sizes are faster than those for larger set sizes. RT x set size slopes were computed from target positions 1 – 7 since all set sizes shared those positions. The slope was 58 msec/item. This yields an estimated rate of deployment between 58 and 116 msec/item (depending on models of memory for rejected distractors. We would lean toward the faster – minimal memory – estimate, on the basis of experiments described above).

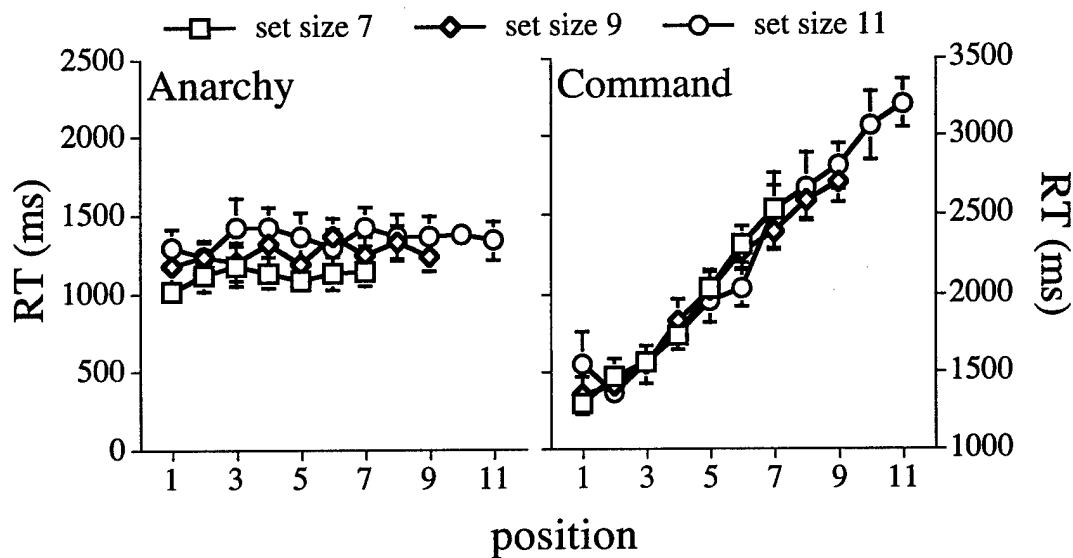


Figure Ten: Average RTs for two varieties of a search for a mirror reversed letter. In 10a, observers search in the usual manner for a single item. In 10b, observers search for the first position (clockwise from 12 o'clock) that contains a mirror-reversed letter. The slope of the RT x target position function estimates the speed of volitionally commanded deployments of attention.

Turning to the Command condition data in 10b, we see that RT is linearly dependent on target position. Set size does not have an effect. The slope of this RT x position function is 196 msec/item, significantly slower than even the most conservative estimate from the Anarchic condition.

To summarize, in a range of experiments, we have estimated the rate at which attention can be deployed in an orderly, commanded fashion. Regardless of our method, the answer is always about the same. Volitional deployments of attention take 200-300 msec per deployment. Estimates of deployment rates in standard visual search are always much

faster, perhaps 20-60 msec/item. Even if we assumed a classic model of sampling without replacement, volitional deployments would be slower than the slowest estimates for anarchic deployments.

General Discussion: Implications and Applications

The evidence from our experiments indicates that memory for previously attended items ~~is of~~ ^{is of} limited if any use in guiding subsequent deployments. Note that this conclusion is confined to the rapid, covert deployments of attention made in visual searches of about one second duration. There is no doubt that a slower, strategic memory has an impact on more extended searches. If you search your kitchen for your keys and move on to the living room, you know that you have searched the kitchen and that knowledge inhibits further searching of the kitchen. Of course, you may return to look again but that is behavior on a completely different time scale than what is under discussion here.

Why not let memory for rejected distractors guide attention? The set of experiments on commanded deployments of attention provide a hint but not an answer. Moving attention on a specific path is a form of memory. This turns out to slow deployment by substantially more than a factor of two. Since the benefit of full memory over sampling with replacement is only a factor of two, the visual system would seem to have concluded that this solution is not worth the time.

The slow speed of planned deployments does not rule out all memory mechanisms. However, the basic explanation may generalize. Memory may not be worth the costs.

One of the aims of this grant is to continue work on the Guided Search (GS) model. Our current work on Guided Search 4 is a logical outgrowth of work on Guided Search versions 1 and 2 (Wolfe, 1994; Wolfe et al., 1989). It is not a direct descendent of GS3 (Wolfe & Gancarz, 1996). GS3 was developed prior to our work on memory for rejected distractors. It was intended to incorporate eye movements into the model. Most real-world searches do not constrain eye movements and most of our data come from experiments in which the eyes are free to move. If you want to keep track of rejected distractors *and* you can move your eyes, then the rejected distractors cannot be marked in simple retinotopic coordinates. Most of the work in GS3 was involved in coordinate transformation, much of it to provide the inhibition of rejected distractors that we then thought was needed. The model is simplified if that requirement is removed.

Of course, we do not know if the design of our attentional mechanisms was limited by the same considerations that influence our efforts to model those mechanisms. But it is certainly plausible that using the entire prior history of a search to govern the next steps in that search was simply too "expensive" and not worth the modest gains in search efficiency. Our results and modeling do suggest that artificial searchers might make use of the same "simple-minded" (and amnesic) principles that human search seems to employ.

Our efforts to put together a comprehensive GS4 model have been slowed by the fast pace of data collection. Each time the modeling gets well underway, we make an empirical discovery that requires that we alter the model. The work on memory in search

seemed to raise one serious problem. How could a system with no memory avoid perseveration. Why wouldn't such a system deploy its attention to the single most salient item over and over again? We have examined this danger by building versions of the Guided Search model that sample with replacement (Wolfe, 2001). The change from sampling without replacement to sampling with replacement turns out not to be particularly problematic. Guided Search creates an "activation map" that rank orders items and deploys attention to the item with the highest activation. For items that are all otherwise equivalent to each other, perseveration is avoided if the model has some dynamic noise that changes the rank ordering of items.

The core of Guided Search is the idea that basic feature information can guide attention. Activation of some items is higher than others because they differ from their neighbors in a "bottom-up" manner (Itti & Koch, 2000; Li, 2002) or because they possess features that are selected as target features in a top-down manner (Egeth, 1977; Egeth, Virzi, & Garbart, 1984; Wolfe, Horowitz, & Kenner, 2003). Guidance is not altered by the lack of memory for rejected distractors. If an observer is looking for red Ts among green Ts and red Ls, attention will be deployed at random among the red items. Even sampling with replacement, the model will not sample green items with low activation.

Sampling with replacement does pose a number of challenges. For example, how would an observer know when to stop and declare the target absent? Our current work tackles such challenges.

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- Wolfe, J. M., Cave, K. R., & Franzel, S. L. (1989). Guided Search: An alternative to the Feature Integration model for visual search. *J. Exp. Psychol. - Human Perception and Perf.*, 15, 419-433.
- Wolfe, J. M., & Gancarz, G. (1996). Guided Search 3.0: A model of visual search catches up with Jay Enoch 40 years later. In V. Lakshminarayanan (Ed.), *Basic and Clinical Applications of Vision Science* (pp. 189-192). Dordrecht, Netherlands: Kluwer Academic.
- Wolfe, J., Alvarez, G., & Horowitz, T. (2000). Attention is fast but volition is slow. *Nature*, 406, 691.
- Wolfe, J. M., Horowitz, T. S., & Kenner, N. (2003). How fast can you change your mind? The speed of top-down guidance in visual search. *Vision Research*, ms.

Personnel Supported

Jeremy Wolfe – PI

Todd Horowitz – Co-investigator

Post-docs who collaborated on this work

Gary Randall (Primary AFOSR support)

Peter Brawn (incidental support)

Aude Oliva (incidental support)

PUBLICATIONS

NOTE: This is not the complete bibliography for the lab for this period but represents those publications with some substantial relationship to the aims of the AFOSR grant.

Published Papers

Wolfe, J.M., Alvarez, G., & Horowitz, T. Attention is fast but volition is slow. *Nature* 2000; 406: 691.

Horowitz, T.S., & Wolfe, J.M. Search for multiple targets: Remember the targets, forget the search. *Perception and Psychophysics* 2001; 63(2): 272-285.

Wolfe, J.M., Oliva, A., Butcher, S.J., & Arsenio, H.C. An Unbinding Problem? The disintegration of visible, previously attended objects does not attract attention. *Journal of Vision* 2002; 2(3): 256-271.

Wolfe JM. 2003. Visual Search: Are some enduring controversies moving toward solution? *Trends Cogn Sci* 7: 70-6

Horowitz, T. S., & Wolfe, J. M. (2003). Memory for rejected distractors in visual search? *Visual Cognition*, 10(3), 257-298.

Submitted Papers

Horowitz, T. S., Wolfe, J. M., & Alvarez, G. (2002). Looking for memory in visual search using attentional reaction time methods. *Cognit Psychol*, submitted 1/02.

Alvarez, G. A., Arsenio, H. C., Horowitz, T. S., & Wolfe, J. M. (2002). Are mutielement visual tracking and visual search mutually exclusive? *submitted 3/02*.

Oliva, A., Wolfe, J. M., & Arsenio, H. C. (2003). Panoramic search: The interaction of memory and vision in search through a familiar scene. *J. Exp. Psychol: Human Perception and Performance*, ms. Submitted 12/02

Papers in Preparation

Horowitz, T. S., Wolfe, J. M., & Alvarez, G. (2003) The speed of free will.

Book Chapters

Chun, M. M., & Wolfe, J. M. Visual Attention. In E. B. Goldstein (Ed.), *Blackwell's Handbook of Perception*, 2001 Vol. Ch 9, pp. 272-310). Oxford, UK: Blackwell.

Moore, C. M., & Wolfe, J. M. (2001). Getting beyond the serial/parallel debate in visual search: A hybrid approach. In K. Shapiro (Ed.), *The Limits of Attention: Temporal Constraints on Human Information Processing* (pp. 178-198). Oxford: Oxford U. Press.

Wolfe, J. M. (2003). The level of attention: Mediating between the stimulus and perception. In L. Harris (Ed.), *Levels of Perception: a Festschrift for Ian Howard* (pp. 169-192). New York: Springer Verlag.

Wolfe, J.M. (2003). Guidance of Visual Search by Preattentive Information. In: L. Itti, G. Rees, & J. Tsotsos (Eds.), *Neurobiology of attention* (Academic Press / Elsevier.

Horowitz, T.S., & Wolfe, J.M. (2003). Visual Search: The role of memory for rejected distractors. In: L. Itti, G. Rees, & J. Tsotsos (Eds.), *Neurobiology of attention* (Academic Press / Elsevier.

INTERACTIONS/TRANSITIONS

Published Abstracts

Horowitz TS, Alvarez GA, Wolfe JM. Desparately seeking memory in visual search. Abstracts of the Psychonomic Society; 2000 Nov; Psychonomic Society Meeting; New Orleans, abstract #15 p. 3.

Alvarez, G. A., Wolfe, J. M., Horowitz, T. S., & Arsenio, H. C. (2001). Limits on multielement tracking. *1st Annual meeting of the Vision Sciences Society, Sarasota, May 2001.*

Wolfe, J. M. (2001). Guided Search 4.0: A Guided Search model that does not require memory for rejected distractors. *1st Annual meeting of the Vision Sciences Society, Sarasota, May 2001.*

Wolfe, J. M., & Hyle, M. (2001). Quitting Time: When is it time to give up in visual search? *Abstracts of the Psychonomic Society*, 6(abs #392), 57.

Horowitz, T. S., Wolfe, J., & Hyle, M. (2002, May 10-15, 2002). Memory in visual search: Do the eyes have it? (abstract). *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL., May, 2002*

Wolfe, J., Torralba, A., & Horowitz, T. S. (2002, May 10-15, 2002). Remodeling visual search: How gamma distributions can bring those boring old RTs to life. *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL., May, 2002*

Horowitz, T. S., Wolfe, J. M. & DiMase, J. S. (2002). Sharing the spotlight: can you search while stream-switching?. *Abstracts of the Psychonomic Society*, 7

Wolfe, J. M. (2002). What guides the deployment of attention in visual search? Old question – new answers. *Meeting of the Psychonomic Society, Kansas City, MO(Nov, 2002).*

Wolfe, J M, Anne Treisman, & Todd S Horowitz: What shall we do with the preattentive processing stage: Use it or lose it? *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL., May, 2003*

Todd S Horowitz, Randall S Birnkrant, & Jeremy M Wolfe: Rapid visual search during slow attentional shifts. *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL., May, 2003*

Jennifer S DiMase, George A Alvarez, Todd S Horowitz, & Jeremy M Wolfe: Constraints on task switching in multielement tracking and visual search. *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL., May, 2003*

Wolfe, J M Modeling Visual Search: Guided Search and Its Friends. *Paper presented at the Munich Symposium on Visual Search. Holzhausen, Germany, June 2003 (Invited Keynote Address)*

Horowitz, T S Partial memory models of visual search. *Paper presented at the Munich Symposium on Visual Search. Holzhausen, Germany, June 2003*

Invited Colloquia (Wolfe)

Columbia U (12/99)	Rutgers U. (2/00)
Boston VA Hospital (12/00)	University College London (12/00)
MIT AI lab (1/01)	Houston - Optometry (2/01)
Rice U (2/01)	Brandeis (4/01)
U. Beijing Graduate School (8/01)	Boston U (9/01)
Schepens Eye Research Inst (9/01)	Vanderbilt U/ (Nashville, TN, 4/02)
Boston U Med School (Raviola Lecture, 4/02)	Wright-Patterson AFB (7/02)
Georgia Tech (10/02)	

Invited Colloquia (Wolfe)

Columbia
Kyoto, Japan
Tsukuba, Japan

Other Invited Talks (Wolfe)

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| 1999 | talk | Paying attention to attention in the teaching of Psychology. - National Institute on the Teaching of Psychology (NITOP), St. Petersburg, Jan. 1999 |
| 1999 | talk | Vision, attention, and memory. 3rd annual Vision Research conference. Preattentive and Attentive Mechanisms in Vision (7-8 May): Ft. Lauderdale, FL. |
| 1999 | talk | The Deployment of Covert Attention: Two Surprises. NATO RTO/SCI-12 Workshop on Search and Target Acquisition. (21-23 June): Utrecht, The Netherlands |
| 2000 | talk | Post-attentive vision and the illusion of perception. Invited paper presented at the Toward a Science of Consciousness, Tuscon, AZ. (April 11, 2000) |
| 2000 | talk | The unbinding problem. Invited paper presented at the annual meeting of the Psychonomic Society, New Orleans, LA. (Nov 18, 2000) |

- 2001 workshop Change Blindness Workshop, Duke U, May 26, 2001
- 2001 talk From stimulus to perception: "Small is the gate and narrow the road",
Invited Plenary speaker at the Fifth annual meeting of the Association for
the Study of Consciousness. Duke U, May 28, 2001
- 2001 talk Levels of Perceptual Delusion: The problem of post-attentive vision,
invited speaker at 'Levels of Perception' conference in honor of Ian
Howard, York U., Toronto, Ontario June 19-23, 2001
- 2002 talk What are we searching for? Studies in Visual Attention. Presidential
Address at Annual meeting of the Eastern Psychological Association,
Boston, April 9, 2002

Consultations / Transitions

In July, 2002, I visited AFRL at Wright-Patterson AFB (Host: Douglas Brungart) in order to discuss this research and explore the possibilities of research collaborations with the group at WPAFB that is interested in visual and auditory search. The collaboration is moving slowly but shows signs of generating some interesting work on combined visual/auditory search tasks.

I arranged for members of this group to attend the Munich Symposium on Visual Search in June, 2003.

Note also that work done on this grant is related to the airport security concerns of the FAA/TSA.

Inventions and Patents - none

Honors and Awards during reporting period

President:	Eastern Psychological Association	2001-2002
Elected to	Society of Experimental Psychologists	2001
Fellow of the American Psychological Association (Div 1)		2002
Fellow of the American Psychological Society		2002
Fellow of American Assoc. for the Advancement of Science		2002
Promoted to Full Professor (Harvard Med)		2003
Honorary Masters of Arts, Harvard U.		2003

Earlier fellowships

Fellow of the American Psychological Association (Div 6) 1995
Fellow of the American Psychological Association (Div 3) 1999